TECHNOLOGY ADOPTION AND INEQUALITY

A Thesis
Presented to
The Academic Faculty

by

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In Partial Fulfillment
of the Requirements for the Degree
Master of Science in the
School of Economics

Georgia Institute of Technology
May 2008

TECHNOLOGY ADOPTION AND INEQUALITY

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Date Approved: May 2008

TABLE OF CONTENTS

LIST OF FIGURES

CHAPTER I

INTRODUCTION

The prices of technological equipment have seen significant declines in recent decades. In Chapter 2 of this thesis, we examine the evidence and causes of these price declines. Among several factors, we focus on the learning curve effect where the cost of producing technological equipment declines as the cumulative number of produced units increases. In Chapter 3 we review the literature on technology adoption and the timing decisions of such adoptions. We aim to contribute to the literature by examining the timing of technology adoption under price declines. Furthermore, we consider the effect of human capital on such adoption decisions.

We begin in Chapter 4 by developing a model of the timing of technology adoption under an exogenous price decline. Section 4.1.1 considers a single price drop in followed by multiple price drops in section 4.1.2. From the analytical results developed in these sections, we examine the effect of human capital on the adoption decision.

Chapter 5 considers the price of the technological equipment to be endogenous to the model. We run computational experiments to demonstrate the declining price as a function of time. We examine the effect of the distribution of human capital on the price decline and adoption decision of the individuals of the population. We conclude with insights on the relationship between human capital inequality and technology adoption decisions.

CHAPTER II

EVIDENCE AND CAUSES FOR EQUIPMENT PRICE DECLINE

The decline of prices of technological equipment can be observed on many levels. Jovanovic and Rousseau's (21) analysis of general purpose technologies provides compelling evidence for the price decline of two of the most ubiquitous and revolutionary technologies to date, namely, electricity and information technology (IT). Jovanovic and Rousseau argue that as technology improves, the price declines and quality improves. Figure 1 shows the quality-adjusted price of equipment in general relative to the consumer price index. The decline in price appears to be exponential (notice the log-linear scale) as a function of time.

While the price of equipment as a whole appears to decline exponentially, Jovanovic and Rousseau demonstrate further that equipment of specific types, such as motor vehicles and personal computers, also appear to decline in price exponentially, albeit at very different rates. In subsequent chapters we take a more in depth look at the price decline of personal computers.

Price declines can occur for a variety of reasons. Several previous studies have argued that as organizations produce more output, the cost per unit of output decreases due to a learning curve. This phenomenon is commonly referred to as learning-by-doing. Epple and Argote (3) provide a particularly nice summary of learning curves in manufacturing. Instances of learning have been documented extensively in a variety of settings including in the production of aircrafts (15; 13; 5), agricultural technologies (35), semiconductor manufacturing (16), and photovoltaic devices (29), to name a few. Jamasb et al (19) document cases of learning by doing of various electricity

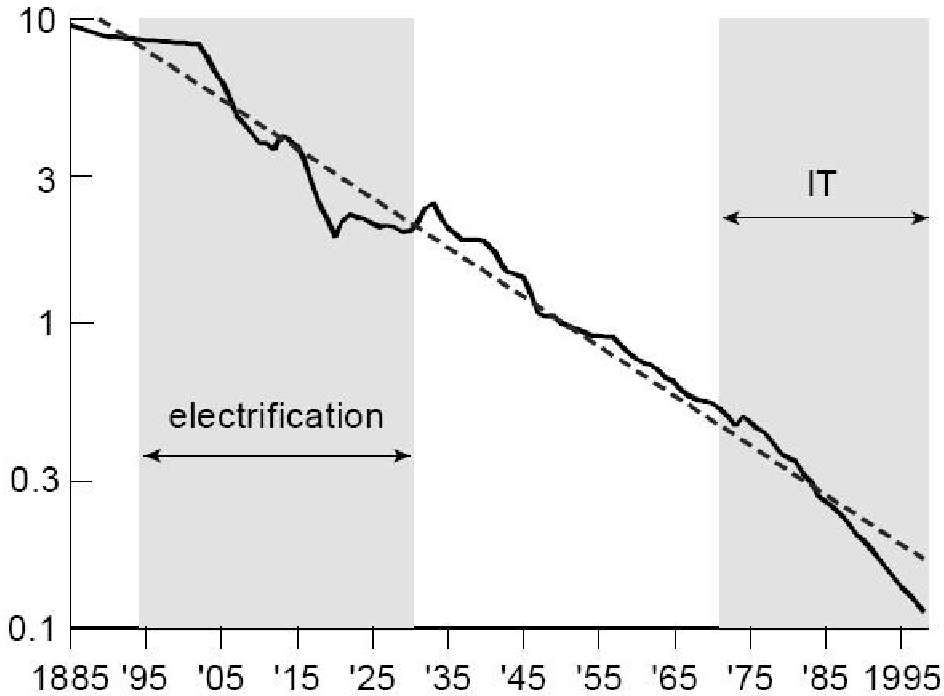

Figure 1: Price decline of equipment relative to consumption goods. Source (21).

generation technologies and finds the rates at which learning occurs. Adler and Clark (1) study the behavioral processes that give rise to the learning curve in an electronic equipment company. Schilling (32) also postulates that a synergy exists between related learning efforts via empirical evidence. Dolan and Jeuland (9) use knowledge of the learning curve to develop optimal pricing strategies.

Sinclair et al (33) analyze 221 specialty chemicals produced by Fortune 500 companies and found a relationship between production experience and unit cost. In this analysis, however, the authors suggest that price declines in these cases may be due to incentives to reduce cost as much as learning-by-doing. Nevertheless, regardless of the cause, as cumulative output increased, unit cost decreased.

Process innovation has also been studied as a key factor in price decline. Hatch (16) examines the relationship between process innovation and the learning curve in the semiconductor industry. In this analysis, learning is actually considered a result of deliberate activities aimed producing lower per-unit costs, rather than an inevitable process acquired through increased production volume. Jovanovic and Nyarko (20) also treat learning as a decision-theoretic problem where workers and managers actively learn how to convert inputs to outputs. The work cites data from several different activities to illustrate varying efficiencies presumably due to difference in learning rates. Product innovations of a producer can translate to process innovations for users of the product.

Other sources of price decline exist. For example, Aizcorbe et al (2) analyze the price decline in the semi-conductor industry. This study finds that of the 24% price decline in a price index for Intel's chip from 1993-1999, 3.5% can be attributed to declines in Intel's profit margins. Aizcorbe also ascertains that a substantial portion of the price decline is due to quality increases associated with product innovation. In the following section we discuss the implications of innovation and learning in how they relate to personal computers.

2.1 Learning Curves in Personal Computers

The personal computer industry has an extremely high level of cost-reducing innovations. Product innovation in semi-conductors largely follows Moore's law. Gordon Moore (27) first predicted in 1965 that the number of transistors that can be "inexpensively" placed on an integrated circuit is increasing exponentially, doubling approximately every two years. This trend has been seen to be true and is generally expected to continue. There are a few papers in the literature that consider this effect as part of the learning curve. Jamasb et al (19) consider the relationship between technical change and learning curves by constructing two-factor learning curves in energy generation technologies where they include the effect of "learning-by-researching" in addition to the traditional learning-by-doing effect. Cumulative R&D *and* cumulative output are considered the main drivers of technology cost reduction. Jamasb et al compute the learning-by-doing and learning-by-research elasticities, to which we allude in subsequent chapters.

Mack (25) considered Moore's law as a learning curve. He postulates that learning in computing power is an industry-wide learning curve, one that follows Moore's law. In other words, there is a constant marginal improvement in the ability to reduce the size of the transistor thereby causing the processor to be smaller, faster, and cheaper. In the world of processors and computers, cost and performance are inseparable and indeed trade-offs. As the industry produces more, it "learns" how to produce smaller transistors (i.e. better performance) thereby allowing the production of previously expensive computers relatively inexpensively. The industry as a whole learns how to produce the same computer cheaper not only by "experience," but by learning how to pack more and smaller transistors on a central processor.

Take for example, the Intel chip 8008 introduced in 1972. The 8008 was an 8-bit processor at 500kHz which had 3,500 transistors at 10 micrometers. Once relatively expensive to produce, the industry today can produce a 64-bit processor with 291 million transistors at 65 nanometers (Intel Core 2). Given such technology available one an imagine how inexpensive it would be to produce a processor today with 3,500 transistors. The price decline of the 8008 processor, as Mack, Jamasb, and Aizcorbe might contend, is not a product of a traditional learning curve (i.e. learning by experience of manufacturing the same product) but by the industry-wide technological learning curve- a learning curve nonetheless.

Figure 2 shows the improvement (measured in transistor size) as a function of time, and more importantly, industry-wide cumulative output. In this way we can see a learning curve in computers where the cost of producing the same computer declines as the industry learns.

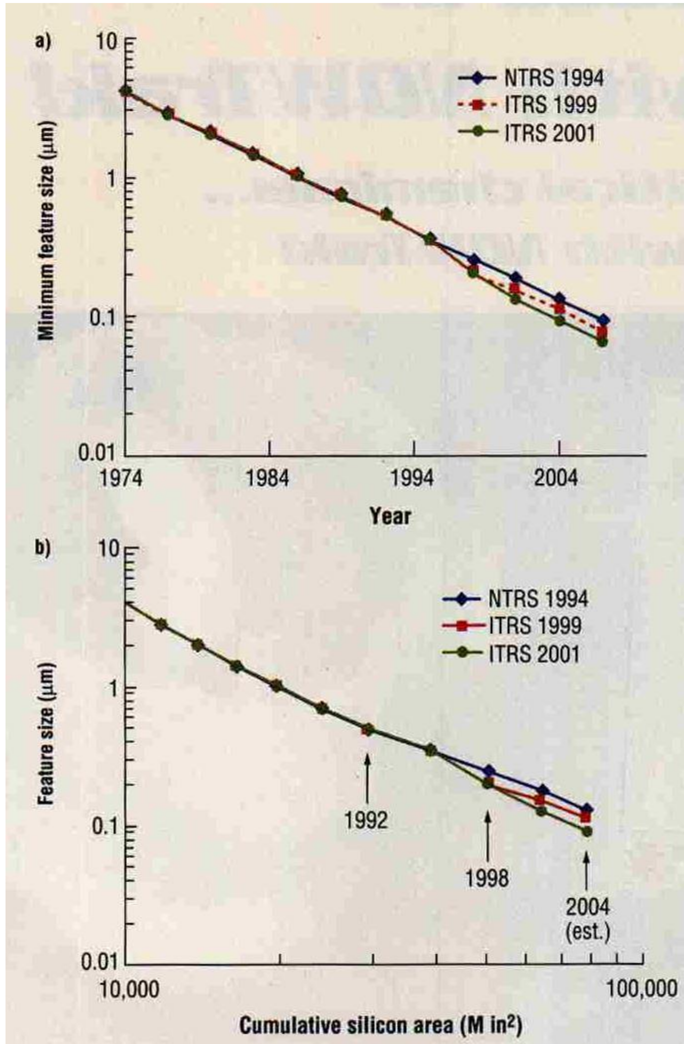

Figure 2: Moore's Law as a learning curve. Source. (25)

In fact, Berndt and Rappaport (6) conducted an extensive study of the change in quality adjusted prices of personal computers. Figure 3 shows rapidly declining prices for both desktops and notebooks.

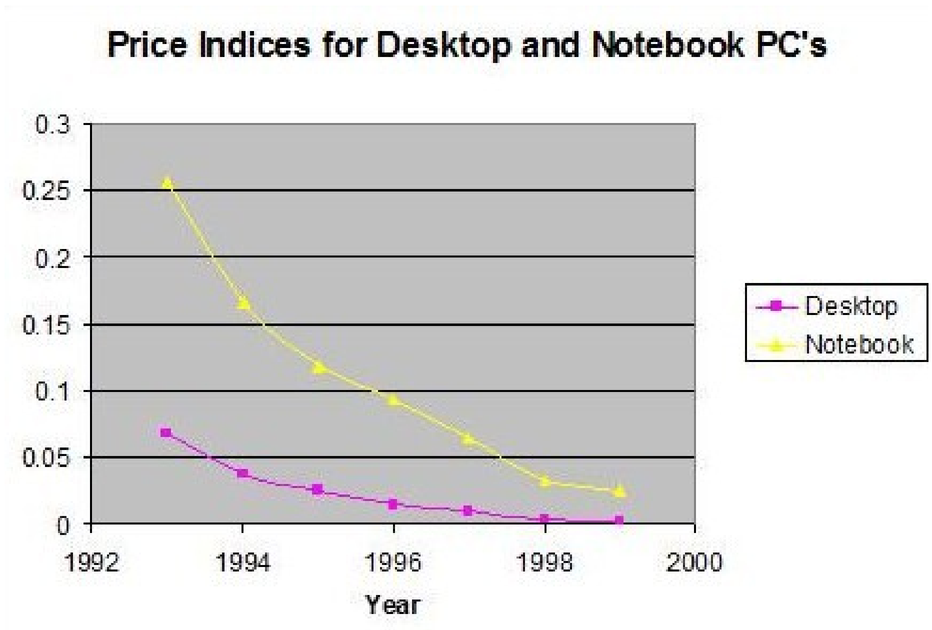

Figure 3: Price indices of PC. Data source (6)

CHAPTER III

TECHNOLOGY ADOPTION REVIEW

3.1 Technology Adoption

Technology adoption and investment decisions have been studied in depth by the economic, finance, engineering, and management science communities, among others. By no means have we conducted an exhaustive review, however the studies mentioned herein provide a representative introduction into the research questions considered and the methods employed. The importance of technology to firms has been well documented. Hu (18) and Mahmood (26) use data driven methods to determine that IT investments contribute to productivity growth in most of the industries in their samples.

Decisions regarding technology adoptions have also been studied extensively in a variety of settings. Quan et al (31), for example, evaluates a duopoly game of information technology investments and how it effects a firm's performance. Kim and Sanders (23) and Fichman (12) use a real options perspective to analyze investment decisions in information technology. Kim develops framework for strategic decisions as well as a basis for valuing IT investments economically as well as a real option, whereas Fichman focuses on determining when a firm should take a lead role in innovation with emerging technologies. Kumar (24) uses asset valuation techniques from the finance literature to assess the value of IT infrastructure investments.

Gopalakrishnan et al (14) considers the factors that effect the adoption of Internet banking at the firm and industry level, in addition to looking at factors external to the industry. Thatcher and Pingry (34) develop both monopoly and duopoly models to analyze the effect of IT investments on firm profit, firm productivity, and consumer welfare under different cost structures. The study finds that both market and cost structure play critical roles. Bardhan et al (4) values and prioritizes a portfolio of projects for an energy utility firm considering several options that require IT investments. By incorporating the impact of project interdependencies, and implementing a real options portfolio optimization algorithm, they arrive a values for each of the projects to determine investments.

3.2 Timing of Technology Adoption

There is less literature on the timing of technology adoptions. Previous studies have primarily focused on timing models of technology adoption where decisions are effected by the arrival time or value of a new technology and/or strategic interaction in the product market. Hoppe (17) provides of an overview of these models. Kauffman (22) considers competition and optimal investment timing together and suggests that the technology adopter should defer its investment until one technology's probability to succeed reaches a critical threshold. Doraszelski (10) also finds that deferring can be optimal by considering an infinite horizon dynamic programming problem of the timing of technology adoption when the arrival of the technology can be either a technological breakthrough or simply a refinement.

Farzin et al (11) use dynamic programming to investigate the optimal timing of technology adoption when speed of the arrival and the degree of improvement of new technologies is uncertain. Bethuyne (7) also considers the timing of technology adoption where technological progress is modeled as geometric Brownian motion. Chambers et al (8) consider levels of investment in technology and includes learning curve effects. This study however is also aimed at competitive decisions under uncertainty of the arrival time of the technology. Mukherji et al (28) and Ngwenyama et al (30) consider the optimal timing of IT upgrades were the decision depends on the technological level.

We are unaware of literature that considers the optimal timing of technology adoption when the decision is effected not by the level of advancement of the technology, but by the declining price of the technology. In the subsequent sections, we aim to contribute to the literature by developing a model with such a goal in mind.

CHAPTER IV

TECHNOLOGY ADOPTION UNDER EXOGENOUS PRICE DECLINE

In this section we analyze the optimal timing of technology adoption when the price of the technology is declining. Evidence of price declines given in Chapter 2 indicate that this may a critical factor in the optimal decision. We use the example of the decreasing price of personal computers.

4.1 Analytical results

4.1.1 Technology adoption under a single price drop

In this section we consider the optimal timing of a purchase of a PC when the price of the PC will drop one time at a specified date.

Define:

- $R(h)$ = dollar value of benefits per unit time of old technology
- $S(h)$ = dollar value of benefits per unit time of new technology
- $c_L e^{-rt}$ = purchase price of technology before price drop
- $c_H e^{-rt}$ = purchase price of technology after price drop
- r = interest rate
- T = purchase date
- h = human capital
- $B(T)$ = present value of discounted benefits

Under the following assumptions:

- $S(h) > R(h)$
- $c_H > c_L$

$$B(T) = \begin{cases} \int_0^T R(h)e^{-rT}\,dt + \int_T^\infty S(h)e^{-rT}\,dt - c_L e^{-rt} & \text{if } T < t' \\ \int_0^T R(h)e^{-rT}\,dt + \int_T^\infty S(h)e^{-rT}\,dt - c_H e^{-rt} & \text{if } T >= t' \end{cases} \tag{1}$$

which evaluates to:

$$B(T) = \begin{cases} R(h)/r - (\frac{S(h)-R(h)}{r} - c_H)e^{-rT} & \text{if } T < t' \\ R(h)/r - (\frac{S(h)-R(h)}{r} - c_L)e^{-rT} & \text{if } T >= t' \end{cases} \tag{2}$$

Since $B(T)$ is monotonic in both of it's intervals, we know that it's maximum will occur at one of the endpoints (i.e. either $T = 0$, $T = t'$, or $T = \infty$). Maximizing B(T) reduces to

$$max\{\underbrace{\frac{S(h)}{r} - c_H}_{T=0}, \underbrace{\frac{R(h)}{r} + (\frac{S(h)-R(h)}{r} - c_L)e^{-rt'}}_{T=t'}, \underbrace{\frac{R(h)}{r}}_{T=\infty}\} \tag{3}$$

The first term represents when $T = 0$, the second term when $T = t'$, the third term when $T = \infty$ (i.e. never adopt) . Essentially, the problem breaks down to two decisions: (1) whether to adopt or not and (2) when to adopt (if adopting at all).

By comparing the third term to the first and second terms to the third term we can see that only when $\frac{S(h)-R(h)}{r} < c_L$ and $\frac{S(h)-R(h)}{r} < c_H$ is never adopting the optimal decision. Since $c_H > c_L$ it is easy to see that if

$$c_L < \frac{S(h)-R(h)}{r} \tag{4}$$

then adopting (at some time) is better than not adopting. Otherwise never adopting is optimal. It remains to determine whether the optimal time to adopt is $T = 0$ or $T = t'$ whenever 4 is satisfied.

First we can clearly see that when

$$c_L < \frac{S(h) - R(h)}{r} < c_H \tag{5}$$

then adopting at $T = t'$ is optimal. When $\frac{S(h)-R(h)}{r} > c_H$ then for the optimal time to adopt to be $T = 0$ we need

$$\begin{aligned} \frac{S(h)}{r} - c_H &> \frac{R(h)}{r} + (\frac{S(h) - R(h)}{r} - c_L)e^{-rt'} && (6) \\ \frac{S(h)}{r} - c_H &> \frac{R(h)}{r} && (7) \end{aligned}$$

Since $\frac{S(h)-R(h)}{r} > c_L$ the fist condition implies the second. Hence we only need to verify the first condition which can be re-written as

$$v - c_H > (v - c_L)e^{-rt'} \tag{8}$$

where we define

$$v = \frac{S(h) - R(h)}{r} \tag{9}$$

Consequently, the optimal time to adopt when 5 is satisfied is:

$$T = \begin{cases} t' & \text{if } t' <= \frac{1}{r} \ln \frac{v-c_L}{v-c_H} \\ 0 & otherwise \end{cases} \tag{10}$$

We can call $\frac{1}{r} \ln \frac{v-c_L}{v-c_H}$ a threshold t, or t*. Now, we can examine the adoption of technology as a function of human capital. Suppose $S(h) - R(h)$ is increasing in h. This corresponds to higher levels of human capital resulting in increased benefits for newer technologies. Under this scenario, as h increases, t* decreases. In other words, those with larger h are more likely to adopt and adopt sooner.

It is interesting to note that the decision to adopt or not is independent of the time of the price drop; it is only dependent on the reduced price and the benefits of adopting/not adopting. Also, all else being equal, when adoption is beneficial, if the price drop occurs sooner rather than later, then the optimal adoption is more likely to occur later (at the time of the price drop) rather than sooner (at time 0). If the price drop occurs later rather than sooner then the optimal adoption time is more likely to be sooner (at time 0) rather than later (at the time of the price drop).

4.1.2 Technology adoption under multiple price drops

In this section we consider the technology adoption decision under multiple price drops.

Suppose the price of the technology is c_0 at time t_0 and drops to c_1, c_2, c_3 . . .c_n at times t_1, t_2, t_3 . . .t_n respectively. In this case, following the development of the previous section, we can see that the maximum of B(T) reduces to

$$\begin{aligned} max\{ \quad & \underbrace{\frac{S(h)}{r} - c_H}_{T=0}, \underbrace{\frac{R(h)}{r} + (\frac{S(h)-R(h)}{r} - c_1)e^{-rt_1}}_{T=t_1}, \\ & \underbrace{\frac{R(h)}{r} + (\frac{S(h)-R(h)}{r} - c_2)e^{-rt_2}}_{T=t_2}, \\ & . \quad . \quad . \quad , \underbrace{\frac{R(h)}{r} + (\frac{S(h)-R(h)}{r} - c_n)e^{-rt_n}}_{T=t_n}, \underbrace{\frac{R(h)}{r}}_{T=\infty}\} \end{aligned} \tag{11}$$

As in the single price drop case, the first term represents $T = 0$ and the last term represents $T = \infty$ (i.e. never adopt). The terms in the middle represent adopting the technology at times t_1, t_2 . . .t_n.

For the remainder of the development, we consider multiple price drops under the following assumptions:

Assumption 1.

$$t_{i+1} - t_i \quad = \quad t_i - t_{i-1} \qquad \forall i >= 1 \tag{12}$$

$$c_{i+1} - c_i \quad <= \quad c_i - c_{i-1} \qquad \forall i >= 1 \tag{13}$$

In other words, the price drops every $\triangle t$, and the price drops are non-increasing. If $v < c_i$ for all i then the solution is clearly to never adopt. It remains to find the optimal adoption time when there exists an i such that $v >= c_i$. For the optimal adoption time to be $T = t_i$ we need

$$(v - c_i)e^{-rt_i} >= (v - c_j)e^{-rt_j} \qquad \forall j >= 0 \qquad j \neq i \tag{14}$$

Under Assumption I and II, we can verify the condition in 14 by only considering c_{i-1} and c_{i+1}. This can be seen because if we have that

$$(v - c_i)e^{-rt_i} >= (v - c_{i+1})e^{-rt_{i+1}} \tag{15}$$

then

$$\frac{(v - c_i)}{(v - c_{i+1})} >= e^{-r\triangle t} \tag{16}$$

Under Assumption I,

$$c_{i+1} <= \frac{c_i + c_{i+2}}{2} \tag{17}$$

which implies

$$\frac{(v - c_{i+1})}{(v - c_{i+2})} >= \frac{(v - c_i)}{(v - c_{i+1})} \tag{18}$$

and consequently

$$\frac{(v - c_{i+1})}{(v - c_{i+2})} >= e^{-r\triangle t} \tag{19}$$

In words, this means that when purchasing the new technology at price c_i is better than at price c_{i+1}, then purchasing at price c_{i+1} is better than c_{i+2}. This implies that purchasing at c_i is better than at c_{i+2}. This is a consequence of Assumption 1.The same process can be followed to show that the same is true for c_{i+3} and so on. The same process also applies to show that when purchasing the new technology at price

c_i is better than c_{i-1}, then it is also better than c_{i-2} and so on. Consequently, under Assumption I, to find that adoption at any given price is optimal, we only need to compare it to adoption at it's "neighbor" prices. This result is very useful in that it allows us to arrive at a simple expression for the optimal adoption time.

By Assumptions (I, II)

$$v - c_0 >= (v - c_i)e^{-rt_i} \tag{20}$$

suffices for the optimal adoption time to be $T = 0$, which can be re-written as

$$\triangle t >= \frac{1}{r} \ln \frac{v - c_0}{v - c_1} \tag{21}$$

For the optimal adoption time to be $T = t_1$ we need

$$(v - c_1)e^{-rt_1} >= (v - c_i)e^{-rt_i} \qquad \forall i >= 0 \qquad i \neq 1 \tag{22}$$

By Assumption I

$$v - c_1 \quad >= \quad (v - c_0)e^{-r\triangle t} \tag{23}$$

$$v - c_1 \quad >= \quad (v - c_2)e^{-r\triangle t} \tag{24}$$

suffice for $T = t_1$ to be the optimal adoption time, which can be re-written as:

$$\frac{1}{r} \ln \frac{v - c_2}{v - c_1} <= \triangle t <= \frac{1}{r} \ln \frac{v - c_1}{v - c_0} \tag{25}$$

From the above development, we can see that in general, for the optimal adoption time to be $T = t_i$ we need:

$$\frac{1}{r} \ln \frac{v - c_{i+1}}{v - c_i} <= \triangle t <= \frac{1}{r} \ln \frac{v - c_i}{v - c_{i-1}} \tag{26}$$

Finally, putting all of these conditions together we can arrive at the optimal time to adopt, T, as

$$T = \begin{cases} 0 & \frac{1}{r} \ln \frac{v-c_1}{v-c_0} <= \triangle t \\ t_1 & \frac{1}{r} \ln \frac{v-c_2}{v-c_1} <= \triangle t <= \frac{1}{r} \ln \frac{v-c_1}{v-c_0} \\ t_1 & \frac{1}{r} \ln \frac{v-c_3}{v-c_2} <= \triangle t <= \frac{1}{r} \ln \frac{v-c_2}{v-c_1} \\ & \quad . \\ & \quad . \\ & \quad . \\ t_i & \frac{1}{r} \ln \frac{v-c_{i+1}}{v-c_i} <= \triangle t <= \frac{1}{r} \ln \frac{v-c_i}{v-c_{i-1}} \\ \infty & otherwise \end{cases} \tag{27}$$

With several price drops, rather than having one threshold value for the time at which the price drop must occur, we can see from 27 that there are ranges for the value of the time between price drops that determines the optimal time to adopt. In other words $\triangle t$ becomes a key parameter. For fixed human capital and price values, the smaller the interval between price drops, the later the optimal adoption is (and vice versa) since one will wait for the price to drop. For a fixed price schedule of several price drops, the higher the human capital the sooner the optimal adoption. These are in line with the single price drop results. A result that we could not see from the single price drop is that as human capital increases, the optimal decision becomes more sensitive to the value of the time interval between price drops.

CHAPTER V

TECHNOLOGY ADOPTION UNDER ENDOGENOUS PRICE

In this section we extend the previous results to incorporate an exogenous price. Specifically, the price of the new technology is governed by a learning curve. Section 2 introduced the concept that prices for technology drops in part due to a learning curve. That is, as more units are produced the marginal cost for each subsequent unit decreases due to learning. Learning can occur at the process level, firm level, or even industry level across firms and can be a result of "experience" or research/innovation.

We begin developing the model by assuming the flow of output with the current technology is

$$R(h) = Ah \tag{28}$$

and the flow of output under the new technology is

$$S(h) = Bh \tag{29}$$

where $B > A$

The price of the new technology is

$$p(t) = \overline{P} - (1 - F(\tilde{h}(t)))^{\gamma} \tag{30}$$

where $\tilde{h}(t)$ is the level of human capital of the individual who has waited t periods before adopting the technology, and F is a gamma probability density function over h, $\overline{P}$ is normalized to one. γ is a constant which can be interpreted as the elasticity of price to adoption, or a "learning elasticity." The optimal adoption time for an individual with human capital h_i is determined by solving

$$v(h_i) = max\{\int_0^t Ah_i e^{-rs}\,ds - p_e e^{-rt} + e^{-rt}\int_0^\infty Bh_i e^{-rs}\,ds\} \tag{31}$$

where the maximization is with respect to t, and p_e is the individual's expectation of the price in the following period. p_e is assumed to be a function of $p(t)$. Equation 31 reduces to

$$v(h_i) = max\{\frac{Ah_i(1 - e^(- rt))}{r} - p_e e^{-rt} + \frac{Bh_i e^{-rt}}{r}\} \tag{32}$$

We can see that Equations 30 and 32 are linked by $p(t)$ and p_e. We solve Equations 30 and 32 to find the evolution of the price and the rate of the new technology's market penetration.

5.1 Computational Experiments

We first solve equation 30 using the initial condition on $\tilde{h}$. Then using the computed valued of $p(t)$, we solve equation 32 for each value of h_i. This will give us an optimal adoption time, t, as a function of h_i. We then invert this function to find the threshold value of human capital that adopts the new technology at the current period. The process repeats when we use this computed threshold value of human capital in equation 30 to determine the next $p(t)$. This procedure is performed in MATLAB under the following assumptions:

- $p_e = p(t) * 90\%$
- F is calibrated such that the GINI coefficient of human capital is ~ 0.466, which is the US income GINI coefficient according the most recent census.
- $\tilde{h}(1)$ is set high enough such that less than 5% of the population adopts the new technology in the first period.
- $B = \overline{P} * 5\%$

- $A = \frac{B}{1.05}$

- $r = .03$

According to Berndt (2000) who calculated price indices for desktop and notebook PC's using a composite of the Paasche and Laspeyres indices, notebooks prices decreased by a factor of 10 in the last 6 years of available data, while desktops decreased by a factor of 27. This is shown in Figure 3. We calibrate the model by adjusting γ so that the price evolution of the new technology follows these curves. γ can be interpreted as a learning elasticity. We find that γ must be 0.6 for the Notebook Computers and 0.52 for Desktop Computers for the price decline of the new technology to mimic that of what Berndt et al found of PC's.

The calibrated model's results can be seen in Figure 5 where the "Price of Technology" represents the price decline under a human capital distribution shown in Figure 4 that has a GINI coefficient near that of the US income (0.4367). Figure 6 shows the proportion of the population that has adopted the new technology as well.

In each of the subsequent figures, we plot the results under two different different human capital distributions. We do this by changing the gamma distribution parameters while keeping the mean constant. In each figure, the human capital distribution of f is that of Figure 4, as are the corresponding results. Notice in figure 7 and 9 that, while f and g have the same mean, g represents a more equal distribution of human capital than found today in the US. The GINI coefficient of f is 0.4367, while that of g is 0.3502 in Figure 7 and 0.2095 in Figure 9. Examining Figures 8 and 10 closely we can see that the price of the new technology initially drops faster under f than under g. The first adopters are individuals with high values of human capital. Because f has larger mass at high values of h than g, more people adopt the technology under f in the first few periods. However, as more people adopt, the price begins to decline (due to learning curve effects) and the level of human capital required to purchase

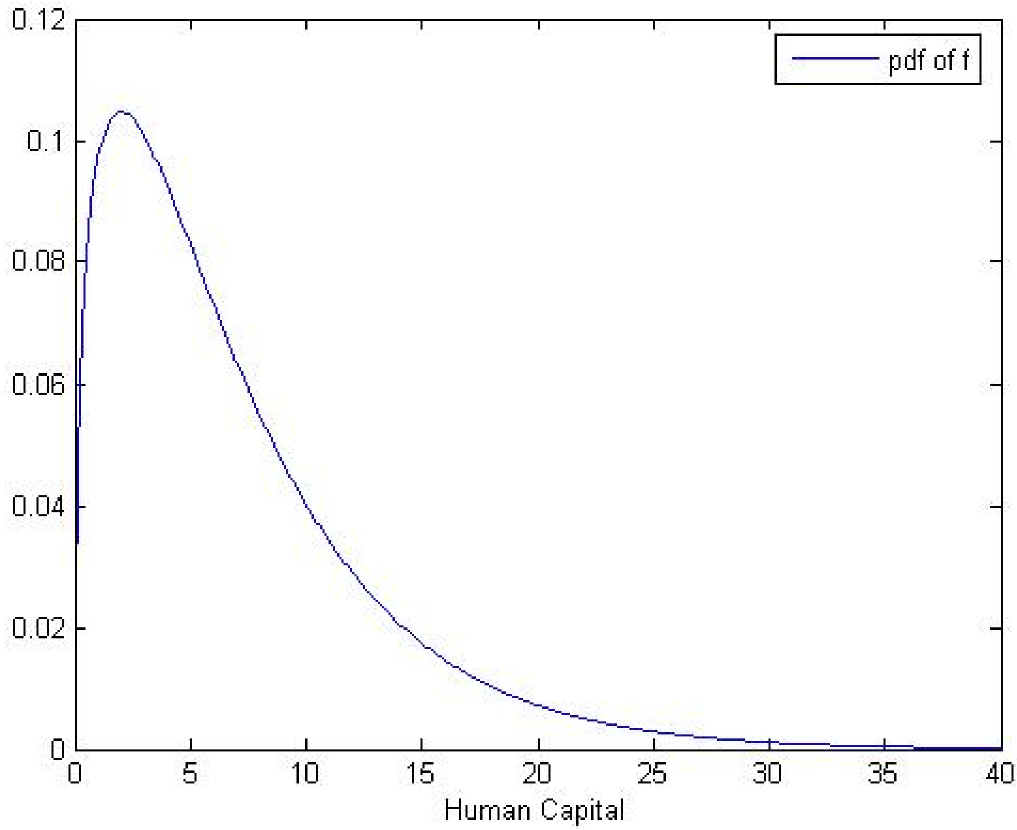

Figure 4: Distribution of Human Capital

the new technology also decreases. Eventually f and g intersect and more people have the required level of human capital for technology adoption under g than under f. Consequently, the rate at which adoption occurs and the prices decline under g surpasses that of f.

However, when we change the human capital distribution so that is is distributed even more equally as seen in Figure 11 so that the GINI coefficient of g is 0.1181 we see different behavior. The price and adoption is shown in Figure 12. Since there are very few individuals with high levels of human capital, few individuals adopt the technology. In fact, so few adopt that rather than the price declining due to learning, the price remains high which subsequently prevents further adoption by those with

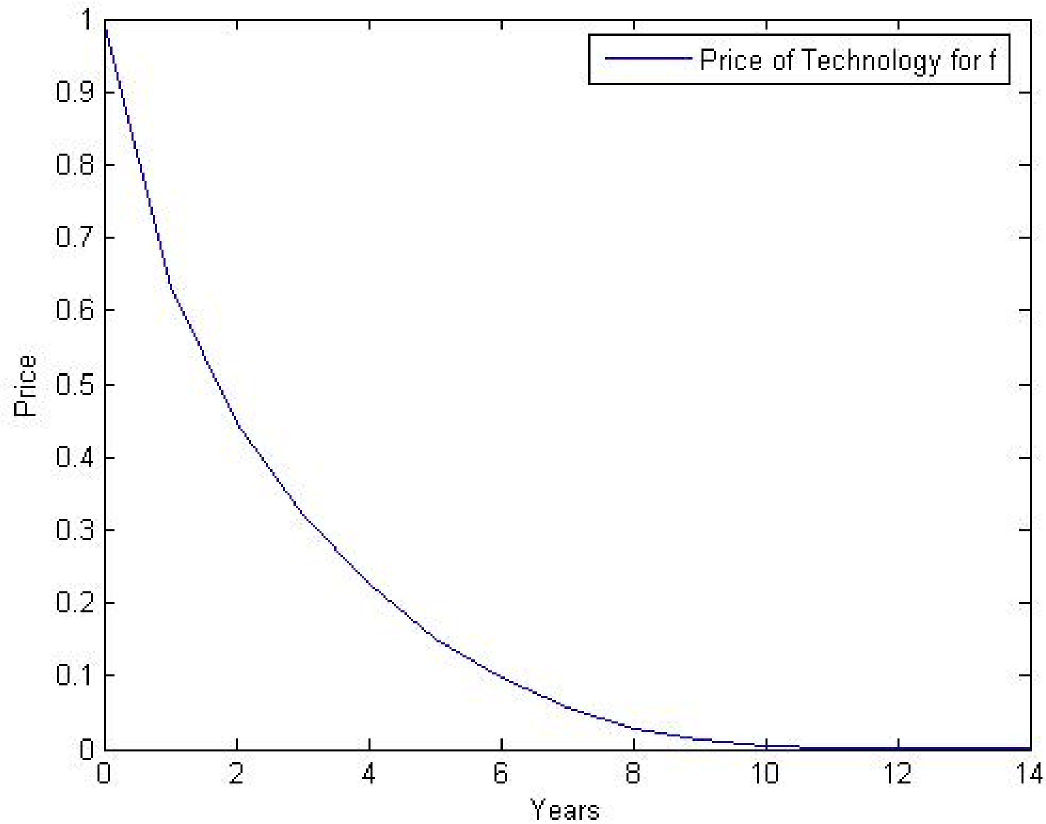

Figure 5: Evolution of Price of New Technology

lower levels of human capital and the product never gets widely adopted.

Next we examine the effect of a larger level of inequality than distribution f. The GINI coefficient of distribution g in Figure 13 is 0.4702 and in Figure 15 it is 0.5465. We can see that when the human capital corresponds to g, the long run price decline is slow. When the inequality is high enough as in Figure 15, the price does not drop below a certain positive value, and only close to half of the population ever adopts.

5.2 Comparison to Other Technologies

Using two factor learning curve analysis Jamasb (19) arrives at learning-by-doing and learning-by-research elasticities for various mature and "reviving" electricity generating technologies. Reviving technologies are those that have been utilized for a long

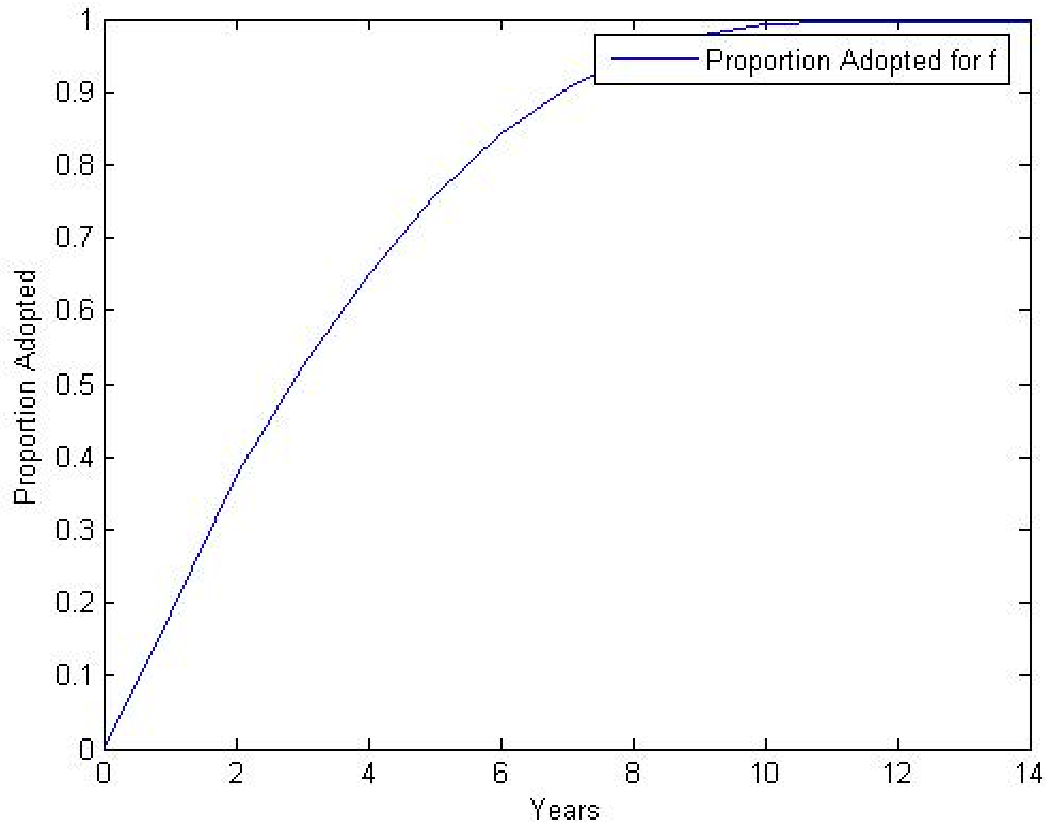

Figure 6: Proportion of Population that Adopts Technology

time and achieved large degrees of technical progress due to favorable opportunities. Mature technologies had learning-by-doing elasticities ranging from 1.96% to 12.39%, where reviving technologies had elasticities ranging from 0.23% to 0.65%. Learning-by-research elasticities ranged from 1.72% to 6.03% for mature technologies and 8.9% to 20.6% for reviving technologies

The overall learning elasticity (which incorporates learning-by-doing and learning-by-research) for personal computers was calculated in section 5.1 to be 60% for Notebooks and 52% for Desktops. Given the large improvements in the *manufacturing* of semiconductor chips as well as the industry-wide technological advances in the *design* of processors, personal computers likely benefit from both learning-by-doing

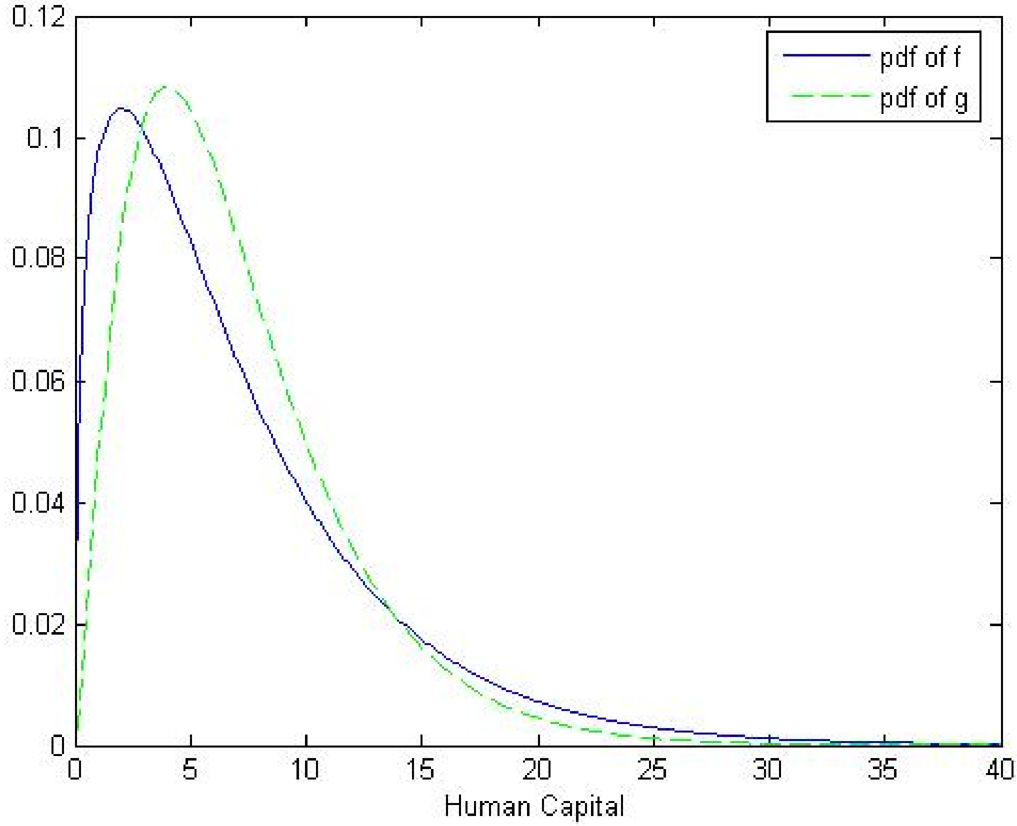

Figure 7: GINI coefficient of g is 0.3502

and learning-by-research in considerable amounts. In this light, and given the unprecedented declines in prices of personal computers, the high learning elasticities computed above are not surprising.

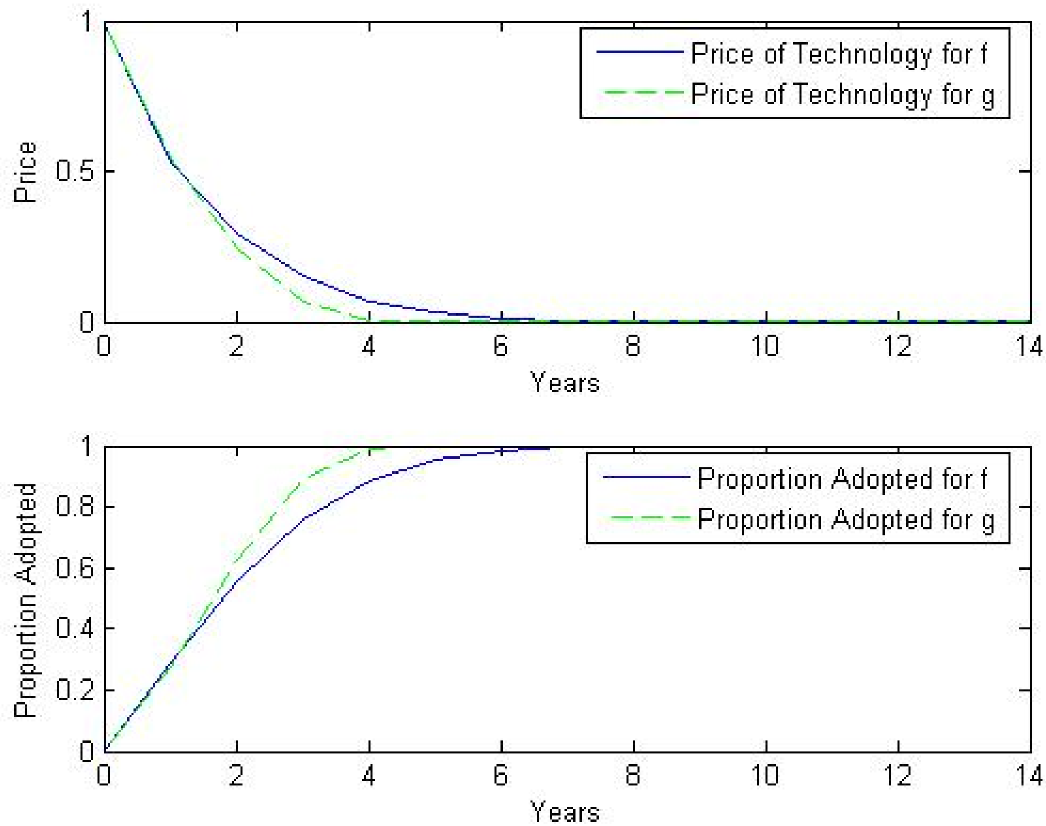

Figure 8: Results when GINI coefficient of g is 0.3502

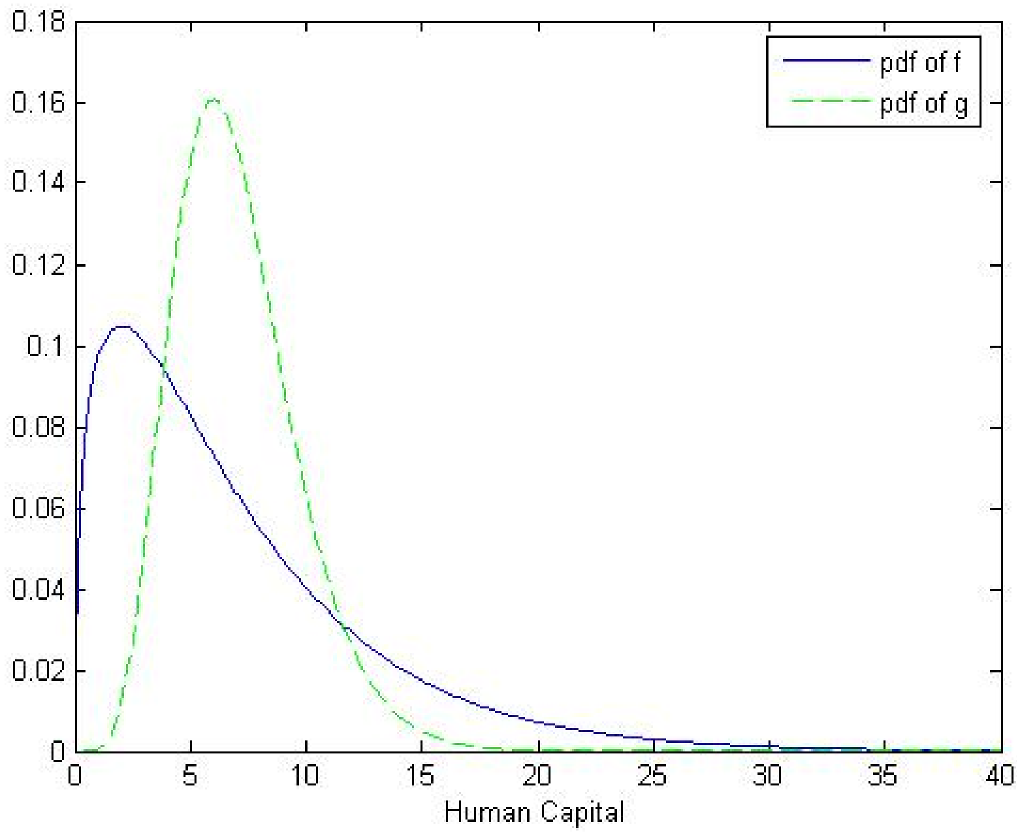

Figure 9: GINI coefficient of g is 0.2095

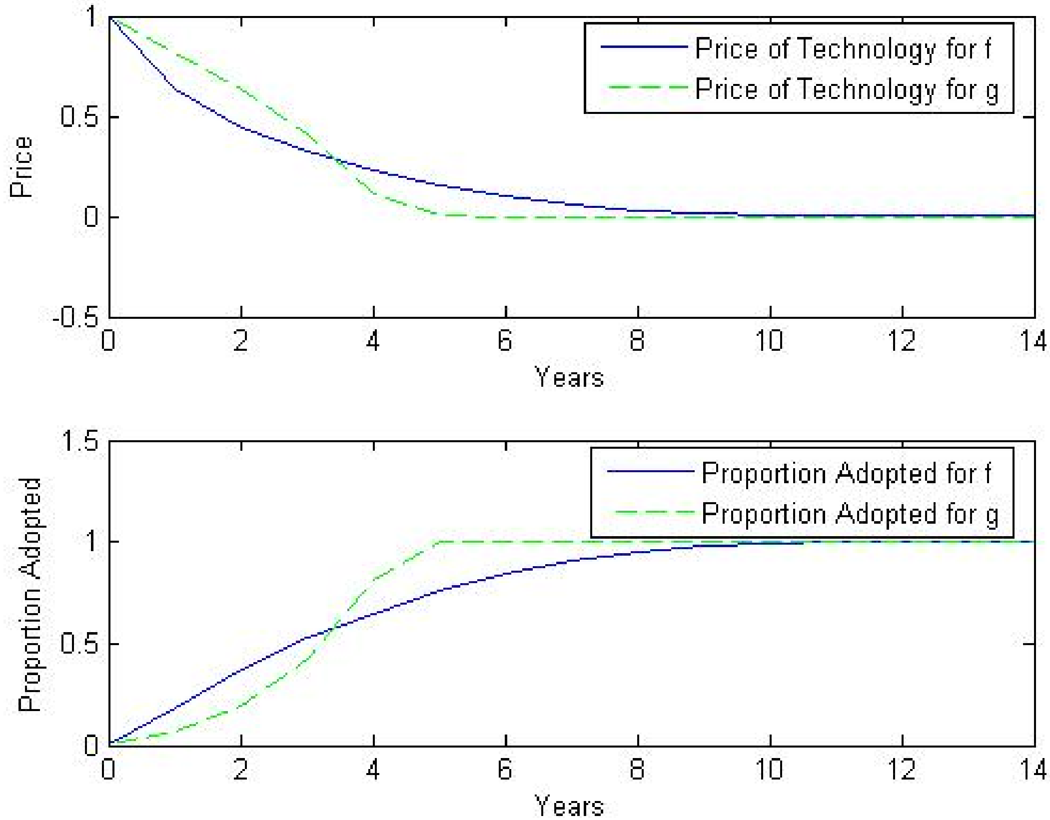

Figure 10: Results when GINI coefficient of g is 0.2095

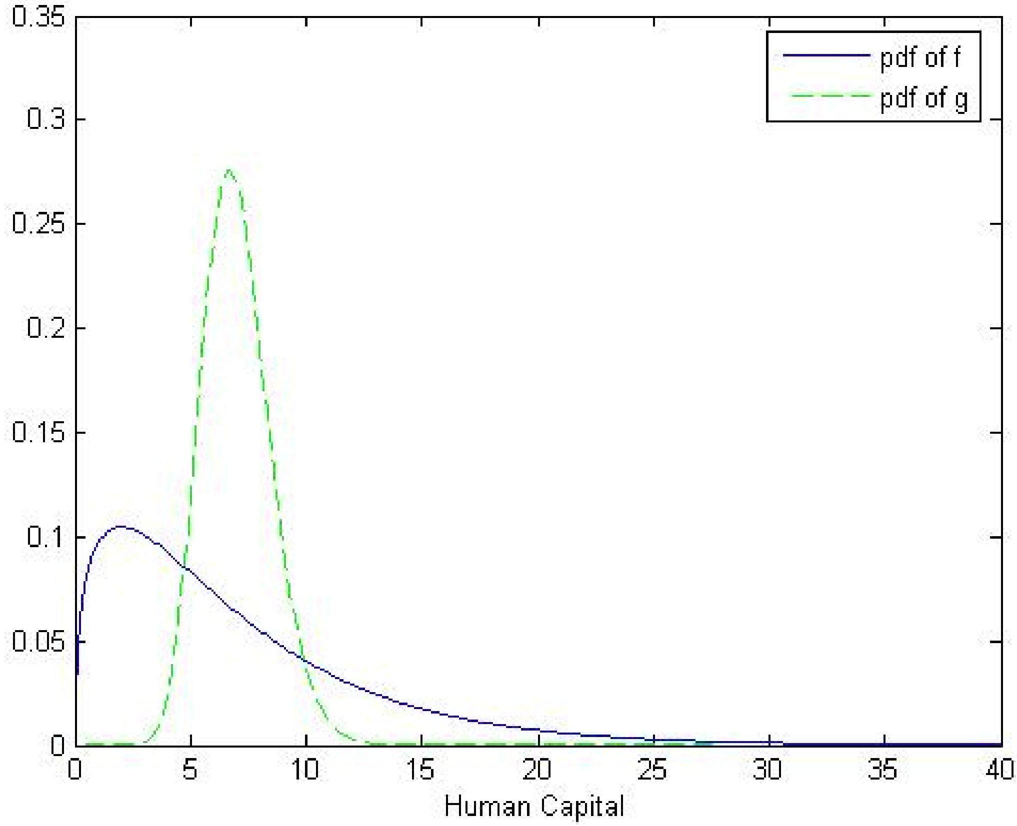

Figure 11: GINI coefficient of g is 0.1181

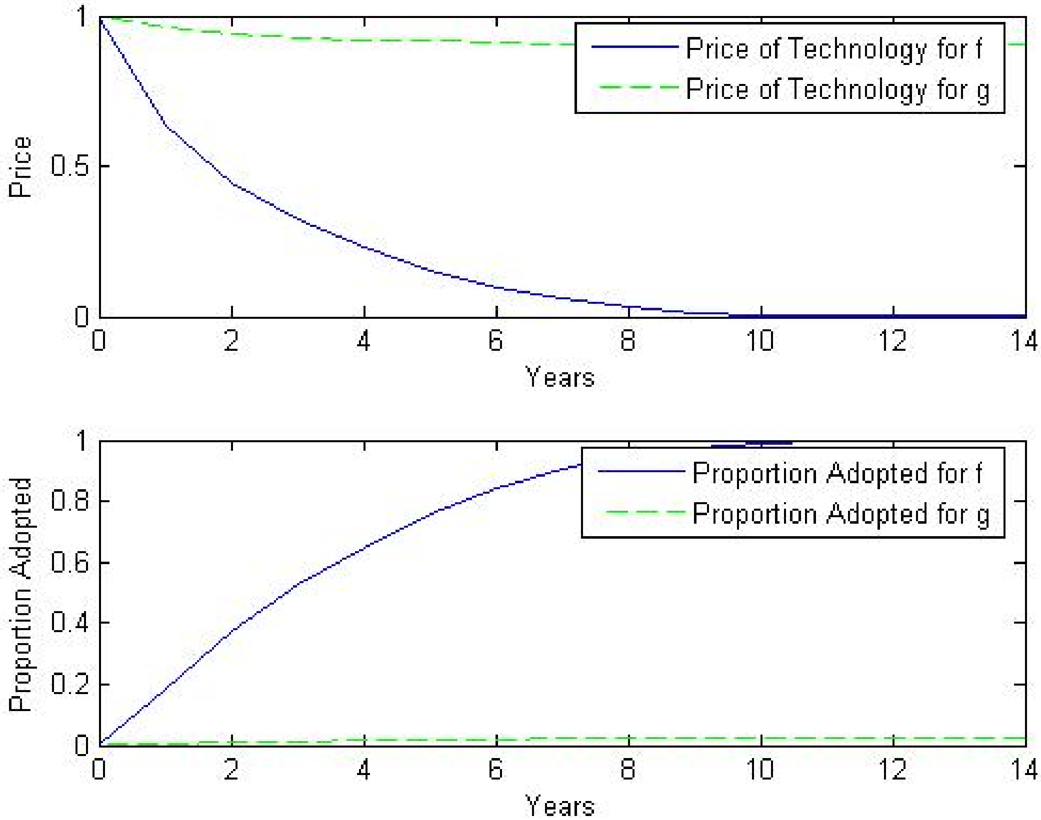

Figure 12: Results when GINI coefficient of g is 0.1181

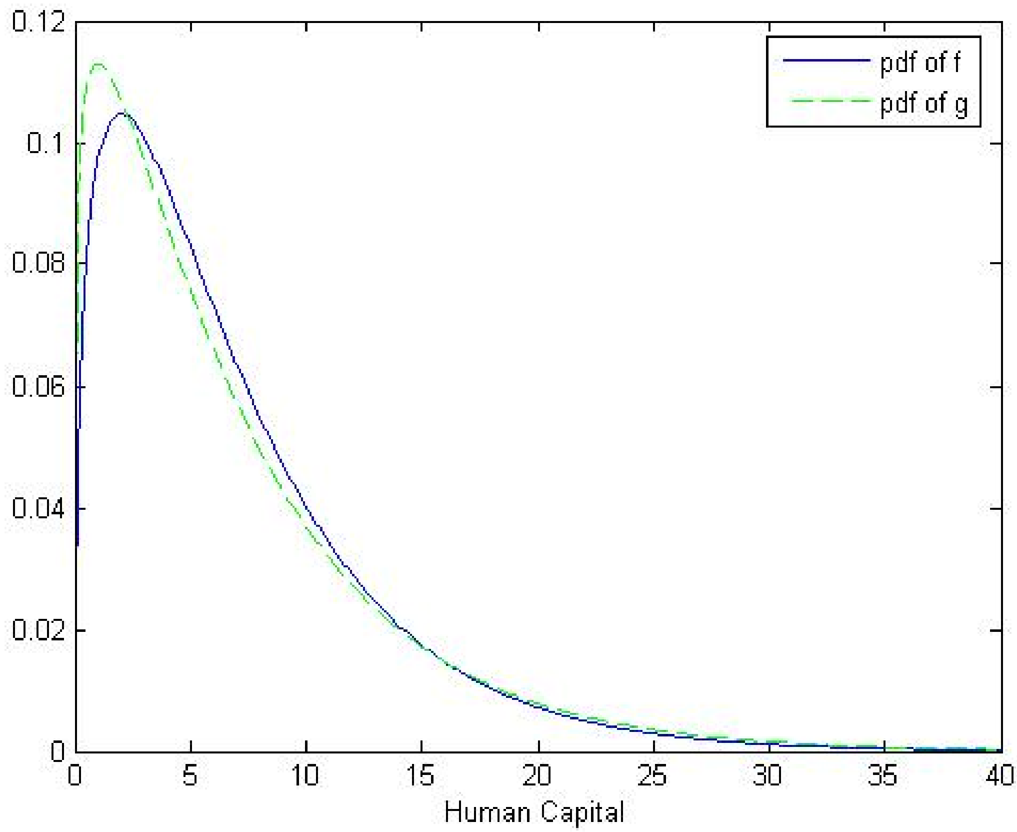

Figure 13: GINI coefficient of g is 0.4702

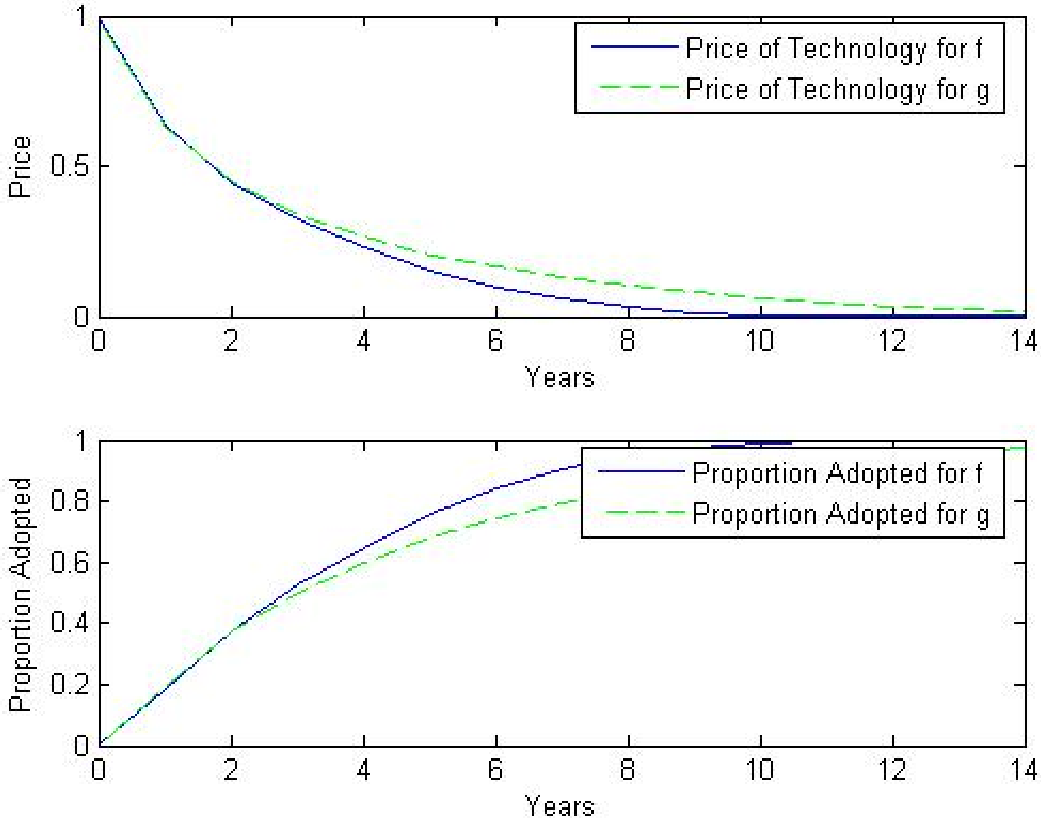

Figure 14: Results when GINI coefficient of g is 0.4702

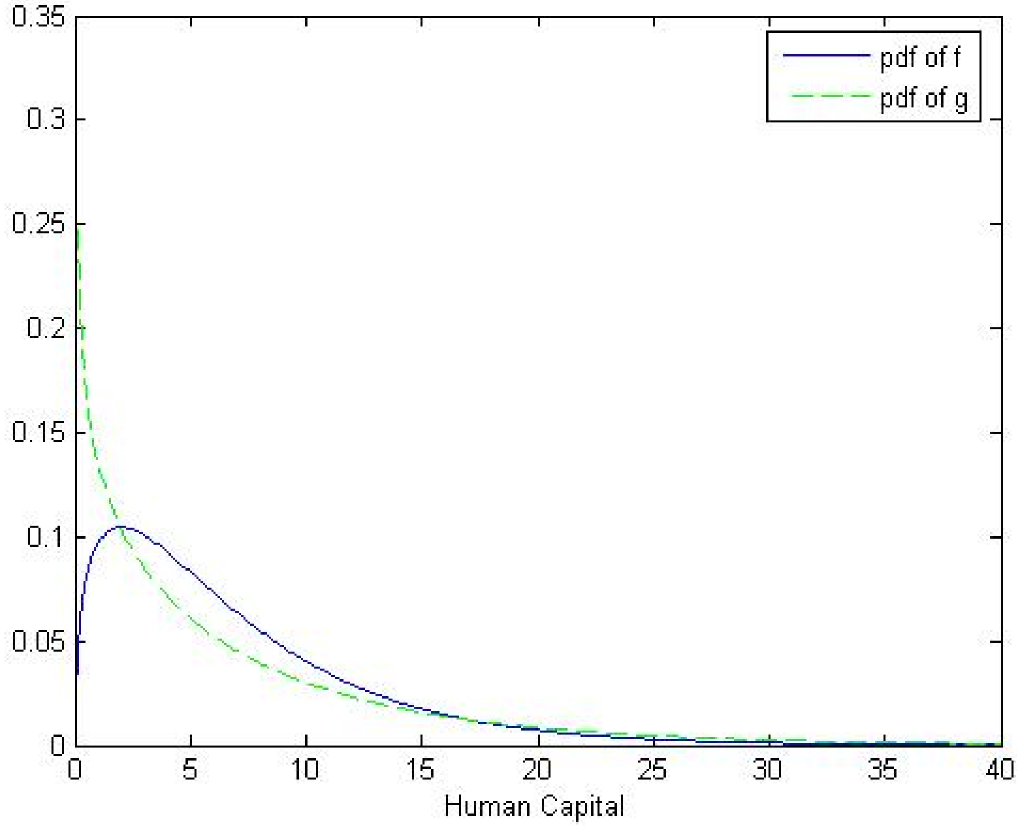

Figure 15: GINI coefficient of g is 0.5465

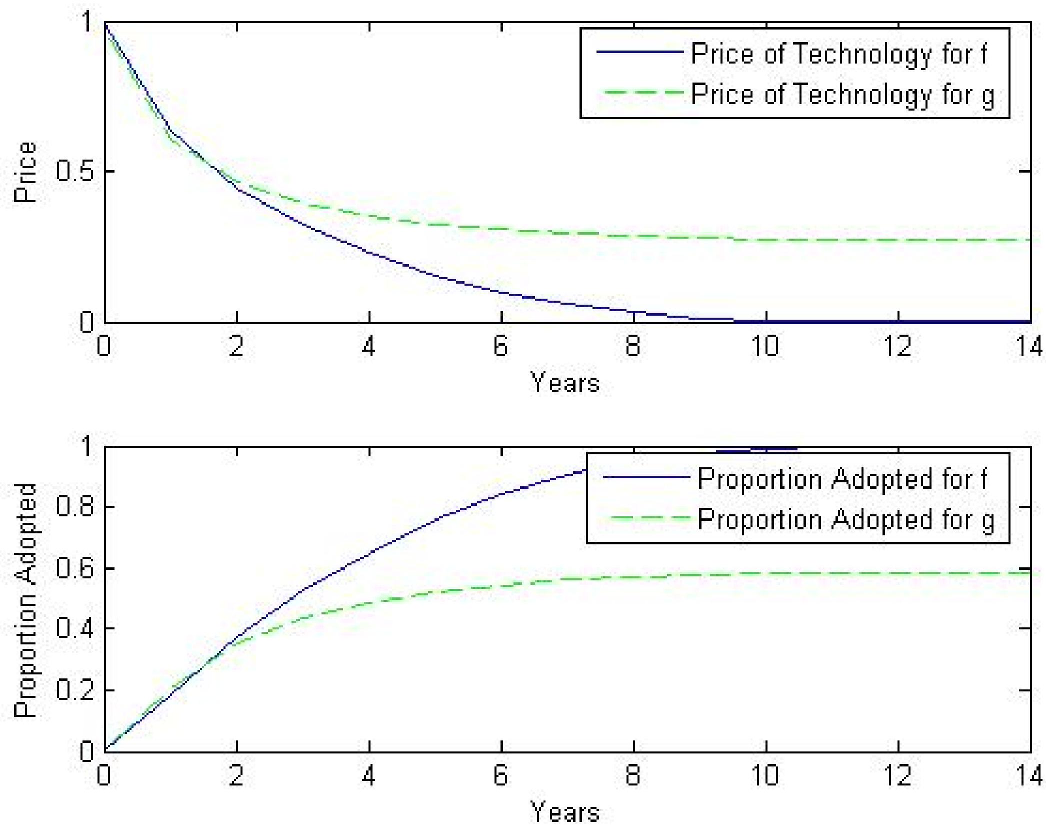

Figure 16: Results when GINI coefficient of g is 0.5465

CHAPTER VI

CONCLUSION

In section 4.1.1 we analyze the technology adoption decision under a single price drop. Analytical results suggest that the adoption decision varies with the level of human capital, and we arrive at a threshold condition that determines the optimal adoption time based on model parameters including human capital. We find that those with larger h are more likely to adopt and adopt sooner. Moreover, the decision to adopt or not is independent of the time of the price drop; it is only dependent on the lower price and the relative benefits of adopting versus not adopting. When adoption is beneficial, if the price drop occurs sooner rather than later, then the adopter is *more* likely to wait for the price to drop before adopting, and vice versa.

In section 4.1.2 we consider multiple price drops and develop analytical results for the special case of when the price drops are evenly spaced and non-increasing. In this case, rather than having one threshold value for the time at which the price drop must occur, we can see from 27 that there are ranges for the value of the time between price drops that determines the optimal time to adopt. Analogous to the result for single price drops, the smaller the interval between price drops, the later the optimal adoption is (and vice versa) since the adopter will be more likely to wait for the price to drop. Also similarly to the case of a single price drop, for a fixed price schedule of several price drops, the higher the human capital the sooner the optimal adoption. One additional result not evident in the single price drop model is that as human capital increases, the optimal decision becomes more sensitive to the value of the time interval between price drops.

In Chapter 5 we examine the case where the price is endogenous. In this case the price decline is more explicitly caused by the learning effect. In other words, as more individuals adopt the technology and more units are produced, the price per unit decreases. We arrive at estimated learning elasticities and compare them to mature and reviving technologies.

We use a gamma distribution to represent the distribution of human capital in the population. Figures 4 - 15 show that the rate of price decline strongly depends on the shape of the distribution of human capital. For example, the distribution in Figure 11 represents a population with a distribution of human capital much more equal than that of the US, but since there are such few people with high levels of human capital the technology is not initially adopted sufficiently to cause the necessary price decline to make it attainable by those with lower levels of human capital. On the other hand, a distribution such as Figure 15 results in close to half of the population ever adopting the technology. Consequently, the results do not suggest that a more or less equal distribution of human capital is more conducive to technology adoption.

The results are more interesting given a more moderate distribution. In this case all of individuals eventually adopt. The effect of human capital on price decline and technology adoption now depends on the time horizon considered. A higher (lower) GINI coefficient results in a slower (faster) longer run price decline and adoption among the population, although a faster (slower) initial price decline as can be seen most clearly in Figure 10.

CHAPTER VII

FUTURE WORK

In future work we aim to more fully develop the endogenous price model presented in Chapter 5. Particularly, we hope to develop analytical insights into the problem, potentially for several distributions of human capital. Extending the computational experiments with further sensitivity analysis would also shed more light on the model's implications.

In addition, we would like to modify the model explore the idea of two factor learning curves since the price of personal computers clearly benefits from both learning-by-doing and learning-by-research. Finally, we would like to use the model for a comparison of the learning curve effects among different industries or products. Specifically, we intend to acquire data on technological equipment prices in the health and medical technologies industries with which will perform similar analysis.

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